A Revised Framework for Analyzing Soil Moisture Memory in Climate Data: Derivation and Interpretation

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ABSTRACT

A revised framework for the analysis of soil moisture memory characteristics of climate models and observational data is derived from the approach proposed by Koster and Suarez. The resulting equation allows the expression of the month-to-month soil moisture autocorrelation as a function of 1) the initial soil moisture variability, 2) the (atmospheric) forcing variability over the considered time period, 3) the correlation between initial soil moisture and subsequent forcing, 4) the sensitivity of evaporation to soil moisture, and 5) the sensitivity of runoff to soil moisture. A specific new feature is the disentangling of the roles of initial soil moisture variability and forcing variability, which were both (for the latter indirectly) contributing to the seasonality term of the original formulation. In addition, a version of the framework entirely based on explicit equations for the underlying relationships (i.e., independent of soil moisture statistics at the following time step) is proposed. The validity of the derived equation is exemplified with atmospheric general circulation model (AGCM) simulations from the Global Land–Atmosphere Coupling Experiment (GLACE).

1. Introduction

Recent modeling and observational studies have highlighted the importance of soil moisture for regional climate (e.g., Betts 2004; Koster et al. 2004b; Seneviratne et al. 2006a; Taylor and Ellis 2006; Hirschi et al. 2011; see also Seneviratne et al. 2010 for an overview). Soil moisture ''memory'' (i.e., persistence) is an important aspect of such land–climate interactions (e.g., Delworth and Manabe 1988; Koster and Suarez 2001, hereafter KS01; Seneviratne et al. 2006b, hereafter S06). In particular, it can contribute to seasonal forecasting of both atmospheric (precipitation and temperature) and land variables (e.g., Schlosser and Milly 2002; Koster et al. 2004a; Lorenz et al. 2010; Koster et al. 2010a,b). It is thus useful to conceptualize the processes that control it.

With this aim, KS01 proposed an analysis framework based on an equation derived assuming a linear dependency of evapotranspiration and runoff on soil moisture and neglecting some higher-order terms. KS01 demonstrated its validity and usefulness, as did subsequent investigations (Mahanama and Koster 2003, 2005; S06). However, the seasonality term—one of the four main terms of the KS01 equation—is not unambiguously linked with soil moisture memory (S06; see also section 2.). Furthermore, in the KS01 version, soil moisture memory over a given time interval is expressed as a function of soil moisture statistics at the following time step. This is a conceptual impediment, as subsequent soil moisture may be viewed as a result rather than a control of soil moisture memory. To address these issues, we present here an extension of the KS01 framework, based on the derivation of an expression for the variability of soil moisture at the following time step. In addition, we propose a version entirely based on explicit equations for the underlying relationships (i.e., independent of soil moisture statistics at the following time step).

2. Equation derivation

a. KS01 equation

KS01 assume that the water balance for the soil column of a typical land surface model, for time period

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$[n, n+1]$ of year (or ensemble member) i, can be written (in the absence of snow) as

$$C_s w_{n+1,i} = C_s w_{n,i} + P_{n,i} - E_{n,i} - Q_{n,i}, \quad (1)$$

where C_s is the column's water holding capacity; $w_{n,i}$ and $w_{n+1,i}$ are the average degree of saturation in the whole column at the beginning and end, respectively, of time period $[n, n+1]$; $P_{n,i}$ is precipitation; $E_{n,i}$ is the total evaporation (i.e., transpiration, bare soil evaporation, and interception loss); and $Q_{n,i}$ is the total runoff (including both surface and subsurface runoff). These latter three variables, $P_{n,i}$, $E_{n,i}$, and $Q_{n,i}$, are accumulated fluxes over the time period $[n, n+1]$. Following the approach of Koster and Milly (1997), KS01 approximate the dependence of evaporation and runoff on soil moisture with simple empirically fitted (semi-implicit) linear functions

$$\frac{Q_{n,i}}{P_{n,i}} = a_n\left(\frac{w_{n,i} + w_{n+1,i}}{2}\right) + b_n \quad \text{and} \quad (2)$$

$$\frac{E_{n,i}}{R_{n,i}} = c_n\left(\frac{w_{n,i} + w_{n+1,i}}{2}\right) + d_n. \quad (3)$$

Here, $R_{n,i}$ is the accumulated net radiation over the period $[n, n+1]$ (normalized by the latent heat of vaporization to have the same units as $E_{n,i}$). The empirically derived, model-specific parameters a_n, b_n, c_n, and d_n are established at each grid point through analysis of the given simulations. The n subscripts indicate that they are derived separately for each time period. Equations (2) and (3) are substituted into (1). Then, by separating w, P, and R into their mean components for the given time of year (indicated by overbars) and corresponding interannual (or intermember) anomalies, subtracting the equation mean and ignoring higher-order terms, the following equation is obtained for the anomalies alone:

$$w'_{n+1,i} = A_n w'_{n,i} + F'_{n,i}, \quad (4)$$

where A_n is a time-invariant factor dependent on the terms $c_n\overline{R_n}/C_s$ and $a_n\overline{P_n}/C_s$,[1] and F_n is a forcing function dependent on P_n and R_n (for details, see KS01). From Eq. (4), KS01 derive the following equation for the month-to-month autocorrelation of soil moisture:

$$\rho(w_n, w_{n+1}) = \frac{\mathrm{cov}(w_n, w_{n+1})}{\sigma_{w_n}\sigma_{w_{n+1}}} = \frac{\sigma_{w_n}}{\sigma_{w_{n+1}}}\left[A_n + \frac{\mathrm{cov}(w_n, F_n)}{\sigma^2_{w_n}}\right]. \quad (5)$$

[1] $A_n = \{[2 - (c_n\overline{R_n}/C_s) - (a_n\overline{P_n}/C_s)]/[2 + (c_n\overline{R_n}/C_s) + (a_n\overline{P_n}/C_s)]\}$.

Equation (5) breaks down soil moisture memory into contributions from four separate terms: 1) $\sigma_{w_n}/\sigma_{w_{n+1}}$, which relates to the seasonality in soil moisture; 2) $c_n\overline{R_n}/C_s$, which relates to variations of evaporation with soil moisture; 3) $a_n\overline{P_n}/C_s$, which relates to variations of runoff with soil moisture; and 4) $\mathrm{cov}(w_n, F_n)/\sigma^2_{w_n}$, which depends on the covariance of the atmospheric forcing with antecedent soil moisture, and thus reflects both the memory of external forcing and land–atmosphere feedbacks.

b. Disentangling of seasonality term

One issue with Eq. (5) is the interpretation of the seasonality term $\sigma_{w_n}/\sigma_{w_{n+1}}$ for two main reasons:

- $\sigma_{w_n}/\sigma_{w_{n+1}}$ can be both high (strong soil moisture control on evaporation or runoff) or low (strong stochastic forcing) in situations of low soil moisture memory (Fig. 1; see also S06), and
- the dependency of this term on $\sigma_{w_{n+1}}$ makes it not easily interpretable, as variability of soil moisture at time step $n+1$ is a result rather than a driver of soil moisture memory.

To address this issue, we derive here an analytical expression for $\sigma_{w_{n+1}}$, which can then be incorporated in (5). This expression is derived from Eq. (4) by taking its square, then the mean over all years (or ensemble members), and finally the square root of the resulting expression. After rearranging some of the terms, this yields

$$\sigma_{w_{n+1}} = \sqrt{\sigma^2_{w_n}A^2_n + 2\sigma_{w_n}A_n\sigma_{F_n}\rho(w_n, F_n) + \sigma^2_{F_n}}. \quad (6)$$

Replacing $\sigma_{w_{n+1}}$ with (6) in Eq. (5) leads to the following reformulation of the KS01 equation:

$$\rho(w_n, w_{n+1}) = \frac{\sigma_{w_n}A_n + \sigma_{F_n}\rho(w_n, F_n)}{\sqrt{\sigma^2_{w_n}A^2_n + 2\sigma_{w_n}A_n\sigma_{F_n}\rho(w_n, F_n) + \sigma^2_{F_n}}}. \quad (7)$$

This equation is equivalent to (5), but provides a conceptually more intuitive interpretation of the drivers of soil moisture memory, as discussed in section 3.

c. Expression based on fully explicit equations and alternative definition of forcing term

To make the final equation fully independent of soil moisture at the following time step, we additionally reexpress Eqs. (2) and (3) explicitly rather than semi-implicitly:

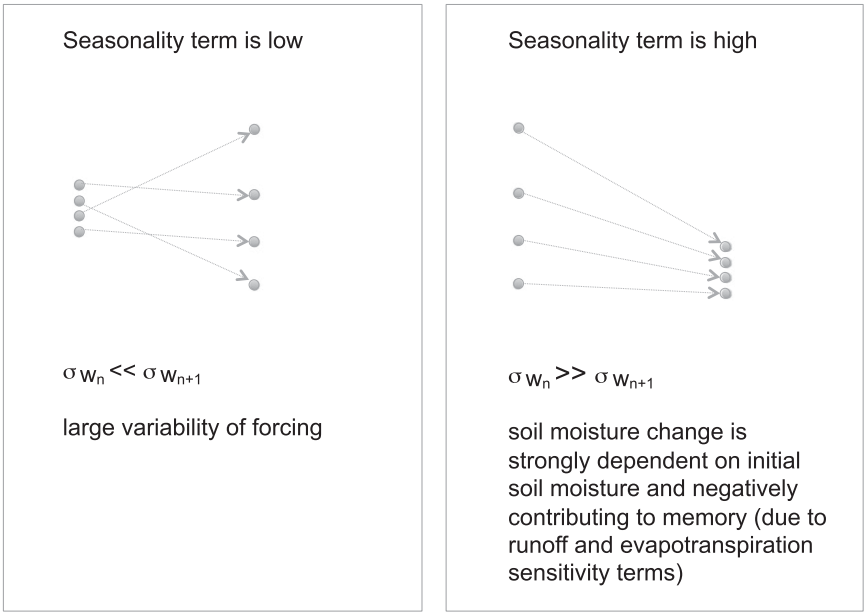

FIG. 1. Illustration of contrasting (high and low) values of seasonality term in KS01 equation for cases of low soil moisture memory.

$$\frac{Q_{n,i}}{P_{n,i}} = a_n w_{n,i} + b_n, \quad \text{and} \tag{8}$$

$$\frac{E_{n,i}}{R_{n,i}} = c_n w_{n,i} + d_n. \tag{9}$$

Using (8) and (9) and following similar steps as KS01 yields the following equation for the soil moisture anomalies at time $n + 1$:

$$w'_{n+1,i} = \left(1 - \frac{c_n \overline{R_n}}{C_s} - \frac{a_n \overline{P_n}}{C_s}\right) w'_{n,i} + \frac{P'_{n,i}(1 - a_n \overline{w_n} - b_n) - R'_{n,i}(c_n \overline{w_n} - d_n)}{C_s}. \tag{10}$$

Equation (10) can also be reexpressed as follows:

$$w'_{n+1,i} = (1 - \alpha_n) w'_{n,i} + \Phi'_{n,i}, \tag{11}$$

with

$$\Phi_{n,i} = \frac{1}{C_s}\left[\left(\frac{\overline{P_n} - \overline{Q_n}}{\overline{P_n}}\right) P_{n,i} - \left(\frac{\overline{E_n}}{\overline{R_n}}\right) R_{n,i}\right], \quad \text{and} \tag{12}$$

$$\alpha_n = \frac{c_n \overline{R_n}}{C_s} + \frac{a_n \overline{P_n}}{C_s}. \tag{13}$$

The new forcing function $\Phi_{n,i}$ [Eq. (12)] is derived using the mean expressions of Eqs. (8) and (9). Using the means of Eqs. (2) and (3), it can also be easily related to the KS01 $F_{n,i}$ function (not shown). Based on Eq. (12), the interpretation of the forcing function $\Phi_{n,i}$ is fairly straightforward: it represents an estimate of changes in relative soil moisture amounts induced by the atmospheric forcing ($P_{n,i}$, $R_{n,i}$) in the given time period n and year or simulation member i assuming a constant sensitivity of runoff and evapotranspiration to soil moisture. We introduce $\Phi_{n,i}$ here instead of $P_{n,i}(1 - a_n \overline{w_n} - b_n) - R_{n,i}(c_n \overline{w_n} - d_n)/C_s$ from (10), which would be the equivalent of the KS01 F_n function when using the explicit equations for (8) and (9), as it makes the forcing function fully independent of soil moisture statistics. It also means that it can be more easily assessed from observations, which can be relevant for some applications.

Following similar steps as KS01, and using the approach from section 2b for the derivation of $\rho_{w_n,w_{n+1}}$ independently of $\sigma_{w_{n+1}}$ yields lastly the following expression:

$$\rho(w_n, w_{n+1}) = \frac{\sigma_{w_n}(1 - \alpha_n) + \sigma_{\Phi_n}\rho(w_n, \Phi_n)}{\sqrt{\sigma^2_{w_n}(1 - \alpha_n)^2 + 2\sigma_{w_n}(1 - \alpha_n)\sigma_{\Phi_n}\rho(w_n, \Phi_n) + \sigma^2_{\Phi_n}}}. \tag{14}$$

This final revised formulation is similar to (7), but is fully independent of information at time step $n + 1$ and uses the newly defined forcing function Φ_n. It may be considered as entirely "explicit" in the context of the seasonal cycle (though based on multiyear statistics), since it is only based on explicit equations for the underlying relationships. Conceptually, both revised versions of the KS01 equation, (7) and (14), are nonetheless equivalent, as they have the same structure and highlight the same drivers for soil moisture memory (section 3). Indeed, their only distinction lies in the replacement of A_n and F_n with $(1 - \alpha_n)$ and Φ_n, respectively. Hence the main conceptual revision in the present framework is the derivation of an expression for $\sigma_{w_{n+1}}$ (section 2b).

3. Interpretation of new equation

a. Main terms of equation

In this section, we provide an interpretation of the newly derived Eq. (14). Five main terms are found to control soil moisture memory in the new formulation:

1) the initial soil moisture variability σ_{w_n},
2) the forcing variability σ_{Φ_n},
3) the correlation between the initial soil moisture and the forcing $\rho(w_n, \Phi_n)$,
4) the sensitivity of evaporation to soil moisture $c_n\overline{R_n}/C_s$, and
5) the sensitivity of runoff to soil moisture $a_n\overline{P_n}/C_s$.

As noted in the previous section, the same five terms also control Eq. (7). Thus, this outcome is a result of the inclusion of the new expression for $\sigma_{w_{n+1}}$ (section 2b), but is not dependent on the choice of semi-implicit versus explicit expressions for Eqs. (2) and (3) [respectively (8) and (9)].

In comparison with the KS01 framework, we find that the revised formulation entails two terms also found in KS01 (items 4 and 5), one term in a modified form (item 3, as correlation instead of the covariance term normalized by the soil moisture variance), and two new terms (items 1 and 2), which were in effect captured jointly in the seasonality term. Nonetheless, because the seasonality term of KS01 uses the subsequent soil moisture variability rather than the forcing variability, it is also affected by the terms 1, 3, 4, and 5, rather than only σ_{Φ_n} and is thus less easily interpreted. Hereafter, we discuss the contribution of the expanded set of five terms to soil moisture memory based on Eq. (14), focusing first on the respective roles of σ_{w_n} versus σ_{Φ_n} (terms 1 and 2) and then on the effects induced by soil moisture feedbacks (terms 3, 4, and 5).

b. Effects of initial soil moisture variability and forcing variability on soil moisture memory

In the absence of feedbacks with soil moisture content—that is, if there are no effects of soil moisture on either evapotranspiration, runoff, or the atmospheric forcing—Eq. (14) simplifies to the following expression:

$$\rho(w_n, w_{n+1}) = \frac{\sigma_{w_n}}{\sqrt{\sigma_{w_n}^2 + \sigma_{\Phi_n}^2}} = \frac{\kappa_1}{\sqrt{\kappa_1^2 + 1}}, \qquad (15)$$

with

$$\kappa_1 = \frac{\sigma_{w_n}}{\sigma_{\Phi_n}}. \qquad (16)$$

In this case, it can be seen from Eqs. (15) and (16) that the critical measure controlling soil moisture memory is the ratio $\kappa_1 = \sigma_{w_n}/\sigma_{\Phi_n}$. Hence, one can distinguish three main situations (see also Fig. 2): 1) cases where σ_{w_n} is much larger than σ_{Φ_n}, which have high memory; 2) cases where σ_{w_n} is much smaller than σ_{Φ_n} (by at least one order of magnitude), which have low memory; and 3) cases where the two terms are of similar magnitude, which have moderate memory.

c. Effects of soil moisture feedbacks on soil moisture memory

In this subsection, we address the effects of the terms $\rho(w_n, \Phi_n)$, $c_n\overline{R_n}/C_s$, and $a_n\overline{P_n}/C_s$ on soil moisture memory as implied by Eq. (14). In particular, we assess the extent to which they modulate the aforementioned effects of σ_{w_n} and σ_{Φ_n}. Within the present framework, we can see that the terms $c_n\overline{R_n}/C_s$ and $a_n\overline{P_n}/C_s$ reduce the soil moisture memory associated with σ_{w_n} because they induce a reduction of the initial soil moisture anomalies (see also discussions in KS01 and S06). This effect is illustrated in the right-hand panels of Fig. 3. On the other hand, the correlation between the initial soil moisture and the forcing $\rho(w_n, \Phi_n)$, if positive, leads to an enhancement of soil moisture memory and thereby (partly) counteracts the effect of the forcing variability σ_{Φ_n}. This may be either due to positive feedbacks or effects of third variables such as sea surface temperatures (e.g., Orlowsky and Seneviratne 2010). Note that Eq. (14) does not exclude the existence of negative correlations between soil moisture and the forcing (e.g., more precipitation following a negative soil moisture anomaly; see also section 4), which contribute negatively to soil moisture memory. The effect of this term when positive is illustrated in the left-hand panels of Fig. 3.

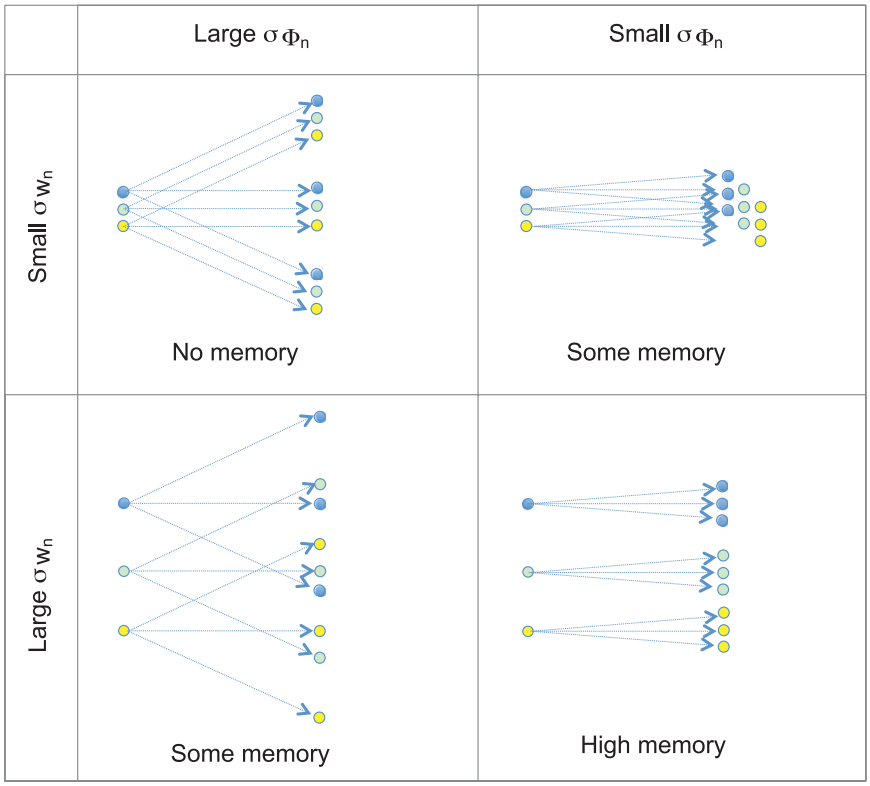

FIG. 2. Illustration of combined effects of the initial soil moisture variability σ_{w_n} and forcing variability σ_{Φ_n} on soil moisture memory, assuming small effects of the correlation of forcing with initial soil moisture $\rho(w_n, \Phi_n)$ and of the evaporation and runoff sensitivity to soil moisture ($\alpha_n = (c_n\overline{R_n}/C_s) + (a_n\overline{P_n}/C_s)$).

Limiting cases of the equation can further exemplify these various effects. If $\rho(w_n, \Phi_n)$ is close to 0, but the terms $c_n\overline{R_n}/C_s$ and $a_n\overline{P_n}/C_s$ are not negligible, Eq. (14) can be expressed as follows:

$$\rho(w_n, w_{n+1}) = \frac{\sigma_{w_n}(1-\alpha_n)}{\sqrt{\sigma_{w_n}^2(1-\alpha_n)^2 + \sigma_{\Phi_n}^2}} = \frac{\kappa}{\sqrt{\kappa^2+1}}, \quad (17)$$

with

$$\kappa = \frac{\sigma_{w_n}(1-\alpha_n)}{\sigma_{\Phi_n}}. \quad (18)$$

In analogy to (15), Eq. (17) relates the autocorrelation of soil moisture to the ratio between the initial soil moisture variability, here modified by the $c_n\overline{R_n}/C_s$ and $a_n\overline{P_n}/C_s$ effects, and the forcing variability over the considered time period. The term κ_1 in Eq. (16) can indeed be seen as a special case of Eq. (18).

Another limit of Eq. (14) is when the term $\sigma_{\Phi_n}\rho(w_n, \Phi_n)$ is much larger than $\sigma_{w_n}(1-\alpha_n)$ (e.g., because σ_{w_n} tends to 0 or α_n tends to 1), for which it simplifies to

$$\rho(w_n, w_{n+1}) = \rho(w_n, \Phi_n). \quad (19)$$

Hence, in that case, all of the memory comes from the correlation of the initial soil moisture with subsequent forcing. Note also that Eq. (14) implies that when $\rho(w_n, \Phi_n)$ tends to 1, soil moisture memory also tends to 1 independently of the values of the other four terms.

4. Application of revised memory equation to GLACE data

In this section, we apply Eq. (14) to AGCM simulations of the Global Land–Atmosphere Coupling Experiment (GLACE). The soil moisture memory characteristics of these simulations were previously analyzed by S06 using the KS01 framework. Therefore, these data provide an ideal test bed for the revised formulation presented here. For a more detailed description of the GLACE project and data, please refer to Koster et al. (2004b, 2006) and Guo et al. (2006). In GLACE, each participating modeling group performed a 16-member ensemble of 3-month (June–August) simulations. Each GLACE simulation was separated into three 27-day

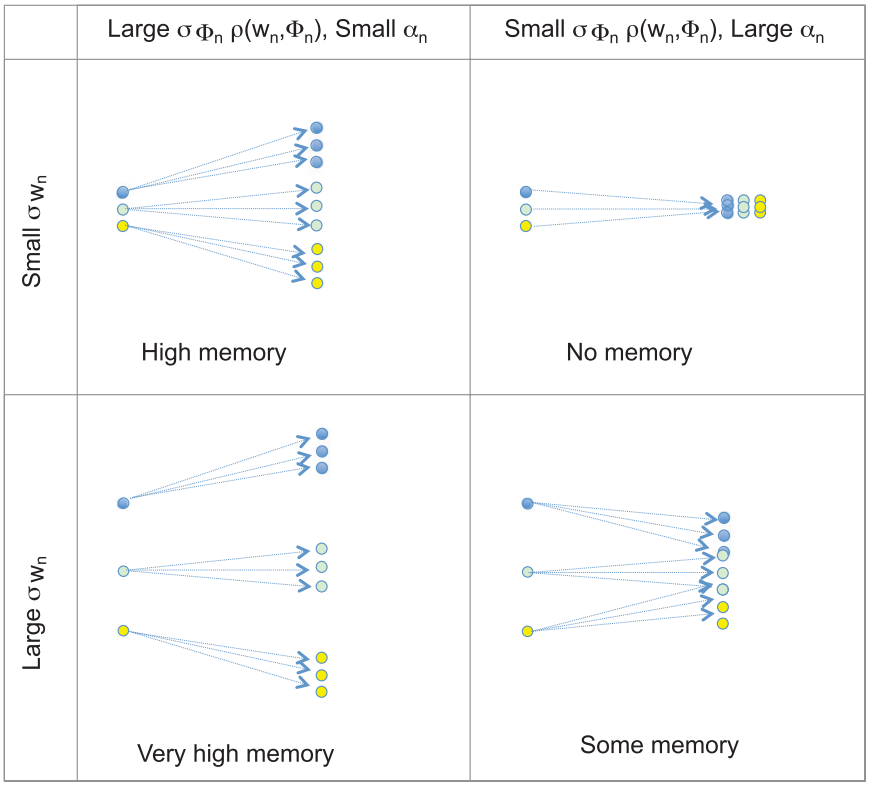

FIG. 3. Illustration of combined effects of the initial soil moisture variability σ_{w_n}, of the correlation of the forcing with the initial soil moisture (assumed to be positive) multiplied by forcing variability $\sigma_{\Phi_n}\rho(w_n, \Phi_n)$, and the evaporation and runoff sensitivity to soil moisture $[\alpha_n = (c_n\overline{R_n}/C_s) + (a_n\overline{P_n}/C_s)]$ on soil moisture memory.

periods (delimited at 9, 36, 63, and 90 days) to produce the data utilized in the present analysis. Details regarding data handling are provided in S06. Note that we do not provide analyses here for the Community Atmosphere Model, version 3 (CAM3) model, which was found to have very low soil moisture variability and anomalous soil moisture memory patterns because of a dry bias (S06).

Figure 4 displays maps of the AGCMs' actual 27-day-lagged soil moisture autocorrelation ρ_{27}, of their estimation from Eq. (14) $\rho_{27_{\mathrm{NEW}}}$, and their differences. The white areas on the plots correspond to regions covered with snow or permanent ice, or to grid points characterized by undefined values (e.g., soil moisture variance equal to zero); note that for the National Aeronautics and Space Administration (NASA) Seasonal-to-Interannual Prediction Project (NSIPP) model, the Andes had not been shaded out in S06. This figure—consistent with the results for the KS01 version (S06)—confirms that for most regions and models, Eq. (14) provides a very good approximation of the AGCMs' soil moisture memory. The inter- and intramodel variations in soil moisture memory are both clearly captured. The slightly more extended blank areas for $\rho_{27_{\mathrm{NEW}}}$ compared to ρ_{27} (e.g., Sahara for NSIPP model) are due to the larger number of factors that may be undefined in (14), such as Φ_n when $\overline{P_n}$ is equal to zero. The few discrepancies, mostly in Southeast Asia [Canadian Centre for Climate Modelling and Analysis (CCCma), Commonwealth Scientific and Industrial Research Organisation Conformal-Cubic 3 (CSIRO-CC3), and the atmospheric component of the third climate configuration of the Met Office Unified Model (HadAM3)] and in the northwestern part of South America [CCCma, CSIRO-CC3, Goddard Earth Observing System (GEOS), and HadAM3], are generally also found with the KS01 formulation (see S06) and overall slightly less pronounced with the revised formulation. A more detailed analysis of the spatial root-mean-square error (RMSE) confirms that the RMSE is generally similar for Eq. (14) and the KS01 version, and overall slightly lower for the revised version with the exception of the CSIRO-CC3 model (not shown).

To investigate the contribution of the different terms of Eq. (14) to the overall soil moisture memory, we display in Fig. 5 the terms $\sigma_{w_n}/\sigma_{\Phi_n}$, $(1 - \alpha_n)$, and $\rho(w_n,\Phi_n)$. In case of low values of $\rho(w_n, \Phi_n)$, (14) can be

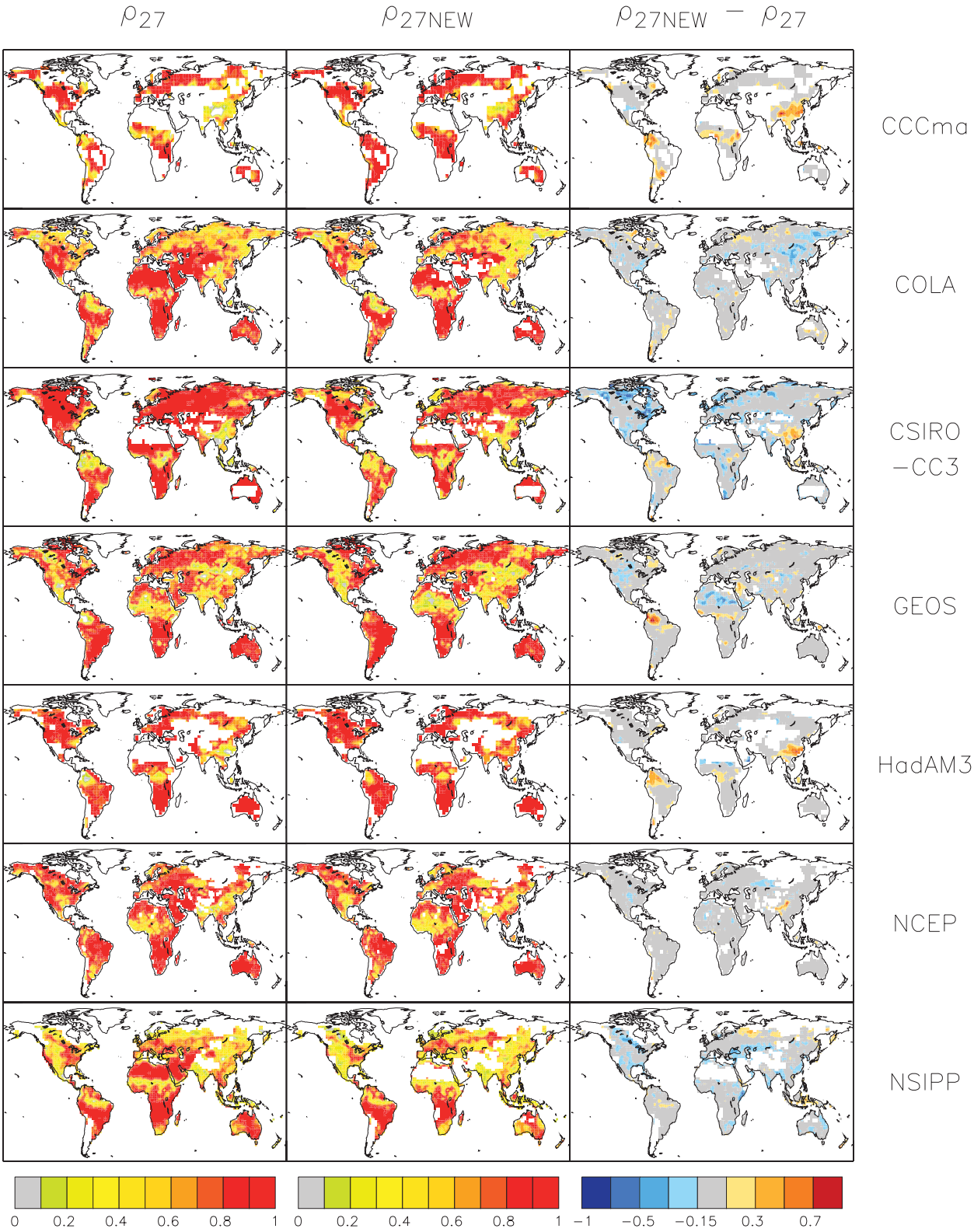

FIG. 4. (left) Maps of simulated 27-day-lagged autocorrelation of total profile soil moisture ρ_{27} in the seven analyzed AGCMs, (middle) corresponding maps of $\rho_{27_{\mathrm{NEW}}}$ as estimated with Eq. (14), and (right) differences (i.e., estimated autocorrelations minus simulated autocorrelations).

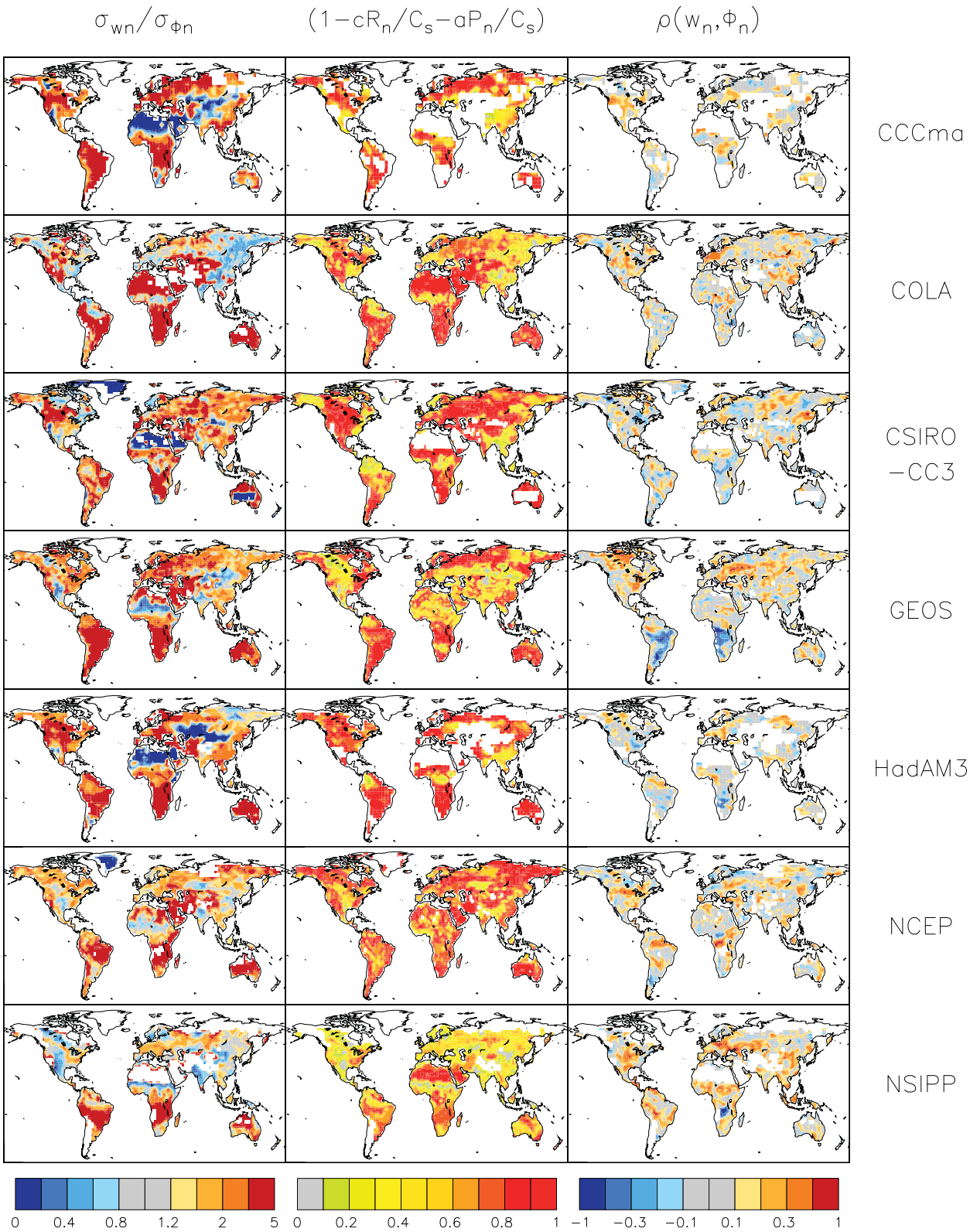

FIG. 5. (left) Maps of $\sigma_{w_n}/\sigma_{\Phi_n}$, (middle) maps of $[1 - (c\overline{R_n}/C_s) - (a\overline{P_n}/C_s)]$ [i.e., $(1 - \alpha_n)$], and (right) maps of $\rho(w_n, \Phi_n)$. Values of $\sigma_{w_n}/\sigma_{\Phi_n}$ that are larger than 5 are set to 5 in the left-hand panels for display purposes.

expressed from the first two terms alone as shown in (17) and (18). When compared with Fig. 4, Fig. 5 clearly shows a strong relationship between these two terms and the actual soil moisture memory in the models. Interestingly, small values of $\sigma_{w_n}/\sigma_{\Phi_n}$ and $(1 - \alpha_n)$, which both imply low memory, are often found in the same regions [in particular in the Center for Ocean–Land–Atmosphere Studies (COLA) model]. But several regions can be identified where one or the other term dominates the overall response. For its part, $\rho(w_n, \Phi_n)$ is overall low, though not inexistent. It generally ranges from about 0.1 to 0.3, and can also be negative in some regions (with particularly large negative values in the GEOS model). This term is generally too small to affect soil moisture memory, with some exceptions: for instance, in the COLA model, it is (positive and) large in Europe, which compensates for a low value of $\sigma_{w_n}/\sigma_{\Phi_n}$. This results in a high soil moisture memory there—both in the simulation results and as inferred from (14).

5. Summary and conclusions

We have presented here a revision of the soil moisture memory equation proposed by KS01. Its main advantage is that it allows the disentangling of the effects of initial soil moisture variability σ_{w_n} and forcing variability σ_{Φ_n} on soil moisture memory, which were previously jointly captured in the seasonality term of the KS01 framework. In addition, the effect of forcing was only implicitly included in the KS01 framework using the soil moisture variability at the following time step, while it is an explicit term of the revised formulation. Finally we also propose a version of the revised equation that is entirely independent of information on soil moisture statistics at the following time step, and we additionally introduce a revised definition of the forcing function, which is independent of any soil moisture information.

The revised framework is useful for assessing the contribution of the different factors controlling soil moisture memory, as illustrated with the analysis of the GLACE simulations and as highlighted by specific limits of the equation. Although the KS01 equation has been so far only applied to model data, both the original formulation and the revised framework presented here could also be applied to observations. While such analyses lie beyond the scope of the present article, this, for example, opens attractive perspectives for model validation. This would be particularly relevant for applications in climate change modeling and seasonal forecasting.

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